

Recent Development of Machine Learning Strategies for Restaurant Review Sentiment Classification: Challenges, Applications, and Opportunities

Keshav Prakash
M_Tech Scholar CSE
TIT (Excellence), Bhopal, M.P
keshavprakash98@gmail.com

Ram Kumar Sahu
Assistant Professor CSE-AIML
TIT (Excellence), Bhopal, M.P
ramkr.sahu@gmail.com

Arjun Rajput
Assistant Professor CSE
TIT (Excellence), Bhopal, M.P
rajarjun07@gmail.com

Corresponding Author: * Keshav Prakash, (keshavprakash98@gmail.com)

Received: 7 October 2026 | **Revised:** 8 October 2026 | **Accepted:** 10 October 2026

Abstract—Online restaurant reviews have grown in number significantly providing an excellent source of customer reviews for analyzing quality of the food, services offered, ambiance of the place, pricing policy and other aspects of customers' dining experience. Hence, restaurant review sentiment classification is a good way to classify customer opinions into positive, negative and neutral sentiments automatically. This review paper gives a comprehensive overview of sentiment analysis techniques used for sentiment classification of restaurant customers' reviews. It gives an insight into the history of development of these algorithms from the feature engineering era to modern ML-based approaches. It explores different types of sentiment analysis techniques, features of restaurant reviews, application areas and challenges of using these algorithms. Comparative analysis of existing research papers on this topic helps to understand their advantages, weaknesses and further perspectives. Thus, it can be seen that while traditional methods of sentiment classification are rather computationally effective, their contextual understanding is quite low in contrast to transformer- and language models-based techniques.

Keywords—Restaurant Reviews, Sentiment Analysis, Natural Language Processing, Machine Learning, Deep Learning, Large Language Models, Aspect-Based Sentiment Analysis.

I. INTRODUCTION

The current generation of consumers depends on online reviews in making informed decisions concerning products and services owing to the development of digital technology. Online reviews have been crucial in the restaurant industry, affecting consumers and businesses. This is due to the fact that millions of people can post their dining experience on websites such as Yelp, TripAdvisor, and Google Reviews, leading to a goldmine of data for restaurants and consumers [1][2]. However, there are several difficulties in manually processing and understanding this enormous volume of textual data. The more evaluations there are, the more difficult it becomes for restaurant managers to read and analyze each one for useful information. It is also difficult to assess general

consumer satisfaction on a large scale since reviews differ in length, content quality, writing style, and sentiment [3].

A natural language processing technology, sentiment analysis has evolved to address these challenges. The purpose of sentiment analysis is to automatically determine if a piece of text suggests a positive, negative, or neutral attitude [4]. Sentiment categorization may assist restaurant managers and owners better comprehending customer attitudes in the context of evaluations, allowing them to make well-informed judgments regarding client preferences, changes, and overall service quality. The system evaluates consumer comments and classifies them as either positive, negative, or neutral sentiment using a number of ML and NLP approaches. A comprehensive evaluation of current methods, their strengths and weaknesses, and knowledge gaps in restaurant review sentiment analysis is further motivated by the ongoing transition from conventional ML to DL, transformers, and LLMs.

A. Structure of the Paper

This is the structure of the rest of the paper. The basics of sentiment analysis for restaurant reviews are laid forth in Section II. Machine learning methodologies and possibilities are covered in Section III. The review of previous research is presented in Section IV. Section V closes the report by summarizing the review's primary results and identifying possible future research topics.

II. FUNDAMENTALS OF RESTAURANT REVIEW SENTIMENT CLASSIFICATION

Sentiment analysis for restaurant reviews uses natural language processing and ML to extract thoughts from reviewers' online comments. It looks at things like meal quality, service, atmosphere, pricing, and customer happiness, and then sorts feedback into good, bad, or neutral attitudes. In order to better serve their customers, restaurants can use this data to learn about their preferences.

A. Sentiment Analysis

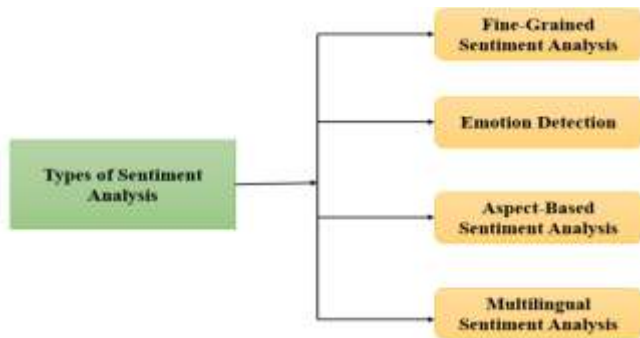


Fig. 1. Several Types of Sentiment Analysis

The phrase "sentiment analysis" can refer to a number of different approaches for finding the degree to which a piece of writing expresses a favorable or negative viewpoint. A time-consuming process is the manual marking of emotional phrases. To automate the sentiment analysis method, two common approaches are used. The sentiment analysis primarily examines three types of sentiment: neutral, negative, and positive. It takes into account the text's intent (exciting or not), emotions and sentiments (glad, sad, furious, etc.), and urgency (urgent or not urgent). Figure 1 shows different types of SA.

- **Fine-Grained Sentiment Analysis:** It offers deeper SA than just positive and negative classification. Sentiment scores or labels expressing differences in sentiment, such as very positive, somewhat positive, neutral, slightly negative, and very negative, are provided instead of only identifying text as positive or negative. It uses sentiment analysis on a variety of newspapers to forecast economic development based on a number of different scenarios [5].
- **Emotion Detection:** Sentiment analysis mainly examines emotions. Different types of feelings, such as happiness, sadness, rage, depression, etc., are represented by other emotions. It is possible to analyze a user's or client's emotions by applying ML or DL algorithms. In some situations, it can be challenging to discern feelings and emotions from SM [6].
- **Aspect-Based Sentiment Analysis (ABSA):** ABSA tries to specify the sentiments connected with several components or people addressed in the text and the overall feeling of the text. For instance, ABSA can collect opinions regarding several product attributes, such as characteristics, functionality, or cost, in a product review [7][8]. ABSA obtained high popularity based on sub-fields belongs to aspect-based sentiment tasks.
- **Multilingual Sentiment Analysis:** SA and sentiment extraction from multilingual text are the main areas of study for NLP. Developing models and methods to evaluate sentiment across languages efficiently is complex in multilingual environments. It entails adjusting to differences in slang, grammar, syntax, cultural quirks, and sentiment expression between languages [9].

B. Applications of Sentiment Analysis

The thoughts and preferences of customers may be better understood using sentiment analysis, which is extensively used in restaurant evaluations. It helps evaluate food quality,

service performance, customer satisfaction, pricing, and overall dining experiences [10][11]. The analysis also supports restaurant recommendation, complaint identification, reputation management, personalized marketing, customer preference prediction, and data-driven business decision-making. Figure 2 depicts the real-world use of sentiment analysis in this section.

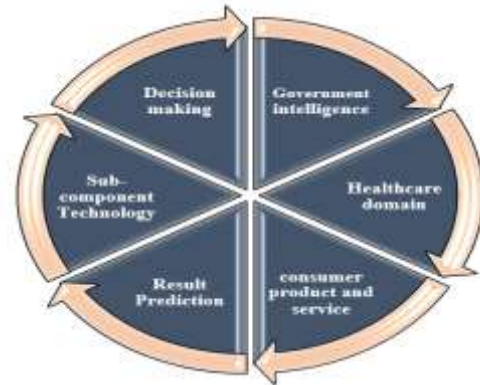


Fig. 2. Applications of Sentiment Analysis

- **Government intelligence:** A plethora of remarks on current events, daily living, and political and social hot topics have emerged with the rise of internet social media [12]. The government may keep an eye on possible public responses by using SA to get opinions on current social issues or policy. The government should take appropriate action or create relevant policies. This research analyzed tweets sent by US municipal governments to determine the extent to which public sentiment shapes their engagement with citizens through social media.
- **Healthcare domain:** An increasing number of healthcare and medical institutions are using SA (sentiment analysis). Professionals in the medical field may use this tool to better serve their patients by collecting and analyzing data on illnesses, adverse medication responses, epidemics, and patient emotions [13].
- **Review of consumer product and service:** In the real world, many automated websites are playing the role of gathering reviews from customers. Example: Google product search [14]. This would meet the demands of both consumers and merchants. The online opinion decides the success or failure of their product. Hence, businesses tend to grab online reviews to improve their product as well as gain customer satisfaction.
- **Result Prediction:** The outcome of an event like election can be predicted. It helps the managers to have a lookout for the voters' views about the various issues and their attitude towards the verbal communication and actions of the candidate.
- **As a Sub-component Technology:** A recommender system typically allows no negative feedback or ratings of online communication to be displayed, whereas the sentiment predictor system identifies a highly negative sentiment.
- **Decision making:** These diverse sources are used by sentiment analysis to locate articles that address the total score. Each stock's favorable and negative sentiment is visually shown by the Stock Sonar.

C. Restaurant Review Characteristics

Restaurant evaluations may be somewhat subjective when it comes to evaluating many aspects such as meal quality, service, atmosphere, cleanliness, pricing, location, and overall eating experience. Customers commonly express satisfaction or dissatisfaction through descriptive comments, ratings, recommendations, and complaints [15]. By analyzing these features (shown in Figure 3), may learn a lot about what customers want, how well restaurants are doing, and whether evaluations are good, negative, or neutral rated using sentiment analysis.



Fig. 3. Restaurant Reviews Characteristic

1) Food Quality

Customers' satisfaction with their dining experience was most affected by the quality of the cuisine, which is a crucial component of every restaurant. emphasized that, from the perspective of the client, food quality is a crucial component in choosing a restaurant. looked at the quality of food as an empirical research demonstrating how important it is in restaurant settings. They find that meal quality and satisfaction/compliance intentions are positively correlated. recently examined how customer pleasure and behavioral intentions are impacted by food quality. Food consistency was determined using a variety of factors.

2) Service Quality

Quality is achieving estimated criteria and their regular maintenance, i.e. a continuing process. This is an intriguing definition of service quality in the hotel sector. With the most broad range of costly hotel services, high-class hotels provide the highest standards and goods. Hotels of the economy class provide a restricted range of services at lower prices and with lower-quality items. The expectation of eating out has changed due to changes in social environment, improved education, a thriving culinary culture, increased knowledge of healthier food options, and cultural influences [16].

3) Customer Experience

Often, companies compete on the experiences they offer consumers, and social networks are very useful for designing those experiences because they have user-generated content about their human experiences. Therefore, information from social networks helps companies create experiences for consumers [17]. Social networks become the most important professional means of communicating restaurant content, enabling them to achieve market positioning. Also, it is necessary to know the expectations of potential customers [18].

D. Challenges of Restaurant Review Sentiment Analysis

Restaurant review sentiment analysis faces several challenges, including sarcasm, irony, ambiguous opinions, and difficulty in identifying sentiment at the aspect level. Multilingual and code-mixed reviews, fake reviews, class imbalance, informal language, spelling errors, negation, limited datasets, and model interpretability further affect the accuracy and reliability of sentiment classification systems.

1) Sarcasm and Irony Detection

The use of irony and sarcasm is an integral part of human communication, with its origins in subtle expressiveness and interpersonal dynamics. Though they are employed differently and have distinct consequences, both occurrences require expressing something that contradicts the intended meaning [19]. The interpretation and comprehension of sarcasm and irony are profoundly dependent on context. Raise awareness of the nuanced dynamics at play in situational irony, which seeks to evoke feelings by defying expectations. Sometimes people confuse irony with sarcasm.

2) Aspect-Level Sentiment Classification

Sentiment Analysis at the Aspect Level is more challenging than Sentiment Analysis at the sentence or Document Levels because it is more difficult to accurately identify the sentiment tendencies associated with specific aspects at the sentence level [20]. The task requires a more precise and intricate algorithm since it pushes the model to comprehend the text more thoroughly and explore the sentiment information linked to certain parts of the phrase.

3) Multilingual and Code-Mixed Reviews

Multilingual and code-mixed restaurant reviews create challenges for sentiment analysis because customers may combine two or more languages within a single sentence. Varying grammatical structures, vocabulary usage, slang, transliteration, and cultural references can lower the efficiency of classification [21]. Therefore, to achieve efficient analysis, multilingual models must be used alongside appropriate pre-processing and various sets of data.

III. EVOLUTION OF MACHINE LEARNING STRATEGIES FOR RESTAURANT REVIEW SENTIMENT CLASSIFICATION

The development of ML techniques for sentiment classification of restaurant reviews can be traced through the shift from traditional ML to DL. This includes the improvement of representation of features, model architecture, and contextual learning.

A. Traditional Machine Learning Approaches

Traditional ML approaches that included NB, SVM, LR, DT, and RF have been mostly utilized in earlier studies concerning restaurant sentiment classification. These types of models use manually crafted features that include TF-IDF, Bag of Words, and n-grams. This approach has limited ability to understand long-range relationships and context in customer reviews, although it is comparatively easy and computationally efficient.

B. Feature Engineering and Text Representation

The efficiency of conventional classifier models is highly dependent upon how the text of reviews is represented. The representation of textual data into numerical representation can be done using TF-IDF, Bag of Words, n-grams, and Word Embeddings [22]. However, these representations might not

be able to capture contextual variations, sarcasm, and negations.

C. Ensemble Learning Strategies

Ensemble Learning uses the output of various ML algorithms to mitigate the flaws of each classifier. There are techniques such as voting, bagging, boosting, random forest, and stacking that improve classification accuracy and stability. These techniques are particularly useful when there is noise or imbalance within text data in restaurant review datasets.

D. Deep Learning-Based Sentiment Classification

The dependence on manual feature creation was reduced once the age of DL arrived. Text reviews may help in automatically training useful representations for CNN, RNN, LSTM, and GRU. While CNNs can detect important local patterns as well as words containing sentiments, LSTM and GRU are particularly suitable for sequential data.

E. Attention-Based Models

This technique was particularly helpful because it helped models focus more on the important words or phrases that are included in the review, thus improving the process of sentiment classification. It is particularly important when it comes to restaurant reviews, where some phrases such as “tasty,” “slow service,” “high prices,” or “friendly staff” can have an impact on the overall feeling.

F. Transformer-Based Approaches

The introduction of transformers was a significant breakthrough in the field of sentiment analysis. Examples of such models include BERT, Roberta, Distil BERT, and domain-specific transformers that employ contextual embeddings to comprehend the connections between words better. What distinguishes transformers from previous sequence-based models is their ability to process context using self-attention mechanisms.

G. Large Language Models (LLMs) for Restaurant Sentiment Analysis

H. Opportunities and Future Research Directions

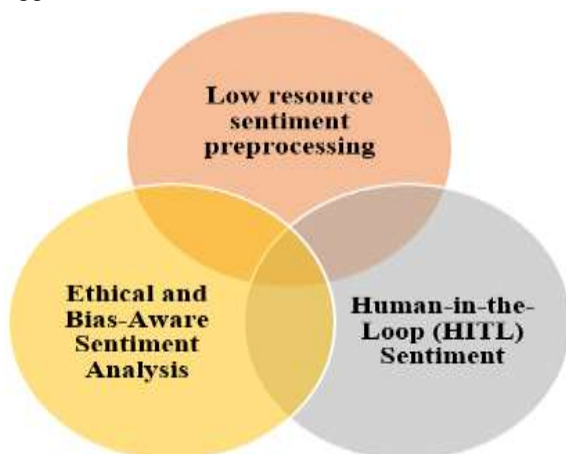


Fig. 4. Future Research Opportunities of Sentiment Analysis

Current studies have focused more on using LLMs for sentiment classification [23]. They facilitate zero-shot and few-shot classifications, and they also help in conducting other complex classifications like aspect-based sentiment analysis, explanation generation, and multilingual

classification. Their ability to interpret complex natural language makes them promising for restaurant review analysis, although computational requirements, hallucination, reproducibility, and domain-specific reliability remain concerns.

1) Low-resource sentiment preprocessing

Future research opportunities (see in Figure 4) include low-resource language analysis, human-in-the-loop validation, robust models for noisy reviews, standardized benchmark datasets, and ethical, bias-aware frameworks for reliable and responsible sentiment classification.

Data pre-processing refers to the preliminary operations performed on data before it is fed into DL models for learning inference and classification. In online chats, on platforms like Twitter and blogs, where slang, misspellings, and multilingual terms are common, it is crucial for enhancing text data [24]. Nevertheless, several pre-processing steps are necessary to reduce morphological complexity, typographical inconsistencies, and noise in some low-resource languages.

2) Human-in-the-Loop (HITL) Sentiment

High-throughput (HITL) is an old concept. One previous use of paid feedback in crowdsourcing through Amazon Turk was to incorporate human input into computer-related processes in order to increase efficacy. Another case in point is the Pay-as-You-Go dataspace, where customers may provide input to help resolve entities that arise during data integration [25]. User Guidance, Few-Shot Learning Active Learning, and Transfer Learning all use the HITL concept.

3) Ethical and Bias-Aware Sentiment Analysis

Ethical and bias-aware sentiment analysis focuses on developing fair and responsible systems that minimize biases in restaurant review classification. Differences in languages, cultures, demographics, and writing styles may affect the model results [26]. Hence, it is crucial to apply various data sources, algorithm transparency, privacy protection, model assessment, and explainability to ensure reliable and unbiased sentiment analysis.

IV. LITERATURE REVIEW

A number of studies have explored the area of sentiment analysis models for predicting consumer opinions, especially restaurant reviews.

Londhe *et al.* (2026) examine the performance of LSTM networks, Multinomial NBs, RNN and many more. It discusses how effective certain approaches are, for instance oversampling and ensemble approaches like Bagging, in dealing with class imbalance issues in restaurant review datasets. Additionally, the study evaluates the impact of word embeddings, specifically Glove, in improving sentiment classification accuracy. The results show that various models and methodologies perform significantly differently when used for restaurant sentiment analysis. This study offers insightful information on how to choose ML models and preprocessing methods for sentiment analysis in restaurant reviews [27].

K and Giri (2025) create a novel SA method with the intention of analyzing customer evaluations in light of their prior interactions. Customer attitudes about hotel services are analyzed using the SA technique to identify NR and PR remarks. Furthermore, approach analyzes texts and provides access to comments. The techniques evaluate the emotion of

large phrases and use SA to break them down into smaller ones, which are then categorized into NR and PR. An algorithm called MNB and another called BNB are used to implement it [28].

Abbas *et al.* (2024) provide a fresh method for detecting ACD in user restaurant reviews using Federated Learning. Accurate classification is accomplished by means of a federated DNN. The data was preprocessed using a variety of methods before the models were trained. This ensured that would have a reliable dataset for classification. In order to forecast models, clean and balance data, and extract TF-IDF features, the proposed approach employs Federated Learning. The suggested method was recommended due to its remarkable 88.38% accuracy for aspect category recognition, as seen in the testing results [29].

Zhu and Cao (2024) examine the use of self-attention-augmented CNNs for the categorization of short texts and provide a dynamic fusion approach. In this study, the CNN and the self-attention mechanism are combined to enhance the model's global comprehension capabilities. The CNN is used to collect local characteristics, while the self-attention method highlights important semantic information. The classification performance is further enhanced by using a dynamic fusion

technique that allows for the real-time adjustment of the fusion degree between CNN and the self-attention mechanism [30].

B. Sunarko, et al. (2023) used to arrange restaurant ratings on Google Maps according to many criteria, including "menu," "taste," "indoor atmosphere," and "outdoor atmosphere," among others. In all, 450 records are utilized by the dataset. The model utilized is BERT, which is constructed on transformer-based neural networks and has the ability to learn grammatical structures, comprehend semantics, and generate relationships among contextual objects. When it comes to accuracy, a score of 41.110/0 is far from satisfactory. For starters, the label annotations of the utilized data contain a multitude of errors. The part titled "Discussion and Conclusion" contains in-depth analysis." [31].

Pleerux and Nardkulpat (2023) used the VADER model to examine Pattaya City, Chon Buri, Thailand, restaurant reviews found on TripAdvisor. The results demonstrate that compared to normal circumstances, assessments were much lower and negative sentiments were more prevalent during the COVID-19 outbreak. The study's conclusions provide insightful information on consumer behavior and needs, enabling restaurant companies to improve service quality, meet customer needs, and make strategic plans for the post-COVID-19 future [32].

TABLE I. COMPARATIVE ANALYSIS OF EXISTING STUDIES ON RESTAURANT CUSTOMER REVIEW SENTIMENT ANALYSIS

Author	Objective	Advantages	Challenges	Recommendation
Londhe et al. (2026)	To evaluate LSTM, MNB, RNN, and ensemble techniques for restaurant sentiment analysis, including oversampling and Glove embeddings.	Compares multiple ML/DL models; addresses class imbalance; evaluates the usefulness of word embeddings and ensemble learning.	Performance varies considerably across models; class imbalance affects classification effectiveness.	Future studies should explore advanced transformer models and more robust imbalance-handling techniques.
K. and Giri (2025)	To analyse customer reviews and classify hotel service sentiments into negative and positive categories using sentence-level analysis.	Handles long reviews by dividing them into smaller sentences; uses MNB and BNB for sentiment classification.	Limited to relatively simple sentiment categories and traditional ML algorithms; contextual semantics may not be fully captured.	Incorporate contextual embeddings and transformer-based models for more accurate sentiment and emotion analysis.
Abbas et al. (2024)	To detect aspect categories in restaurant reviews using federated deep learning.	Combines data cleaning, balancing, TF-IDF, and federated learning; improves privacy while enabling distributed model training.	Achieved 88.38% accuracy, indicating scope for improvement; TF-IDF may have limited semantic representation.	Use transformer-based embeddings and advanced federated learning architectures to improve aspect detection.
Zhu and Cao (2024)	To improve short-text classification by combining CNN with self-attention and a dynamic fusion strategy.	Captures both local features and important semantic information; dynamic fusion improves integration of CNN and attention features.	Computational complexity may increase; approach is designed mainly for short-text classification rather than restaurant-specific reviews.	Adapt the hybrid attention architecture to restaurant reviews and evaluate it against modern transformer-based models.
B. Sunarko et al. (2023)	To classify Google Maps restaurant reviews into categories such as menu, taste, and indoor/outdoor atmosphere using BERT.	Uses BERT for contextual semantic understanding; considers multiple restaurant-related aspects.	Low accuracy of 41.11%, mainly due to inaccurate label annotations; small dataset of 450 reviews.	Use a larger, better-annotated dataset and improve annotation quality before applying advanced models.
Pleerux and Nardkulpat (2023)	To analyse restaurant reviews from TripAdvisor using VADER and examine sentiment changes during and after COVID-19.	Provides useful insights into customer sentiment trends and changing restaurant-service expectations.	VADER is lexicon-based and may struggle with contextual, implicit, or domain-specific sentiments.	Apply context-aware deep learning or transformer models to capture complex sentiment patterns more accurately.

Research Gap: The comparative analysis in Table I shows that existing restaurant review studies have explored traditional ML, DL, attention-based, and transformer models. There are still challenges in dealing with class imbalance, contextual semantics, low annotated datasets, and multi-class sentiment classification. The traditional techniques include MNB, BNB, VADER, and TF-IDF but their context understanding is not good, and the state-of-the-art DL techniques do not have proper comparative analysis.

Therefore, there is a need to come up with a strong method that addresses all the above problems.

V. CONCLUSION AND FUTURE WORK

The current review has analyzed how sentiment analysis has become an efficient instrument in order to analyze customer opinions within the restaurant domain. It is shown that restaurant reviews include a variety of information about food, service, atmosphere, price, and other characteristics that

may be used for the analysis of restaurant's performance. It is shown in the reviewed studies that there has been an evident trend of moving from traditional methods that rely on TF-IDF, NB, and other algorithms to more modern and complex methods, which rely on DL, attention mechanisms, transformers, and large language models. Nevertheless, the comparative analysis of the studies has revealed that there is no method that solves all problems of analysis. Such issues as class imbalance, sarcasm, aspect-level opinions, multilingualism, annotation quality, and limited datasets continue to be relevant for the classification process. In this way, the comparative analysis reveals that contextual models have a better potential to understand customer opinions, while traditional methods may be used in case the computational efficiency is necessary.

- **Funding:** This research received no external funding.
- **Institutional Review Board Statement:** Not applicable.
- **Informed Consent Statement:** Not applicable.
- **Data Availability Statement:** The data supporting the findings of this study are available from the corresponding author upon reasonable request.
- **Conflicts of Interest:** The author declares no conflict of interest.

How to cite this article:

K. Prakash, R. K. Sahu, and A. Rajput, "Recent Development of Machine Learning Strategies for Restaurant Review Sentiment Classification: Challenges, Applications, and Opportunities," *Journal of Global Research in Electronics and Communication*, vol. 2, no. 10, pp. 1–7, Oct. 2026, Doi: <https://doi.org/10.5281/zenodo.23391115>

REFERENCES

- [1] L. Li, L. Yang, and Y. Zeng, "Improving Sentiment Classification of Restaurant Reviews with Attention-Based Bi-GRU Neural Network," *Symmetry (Basel)*, vol. 13, no. 8, p. 1517, Aug. 2021, doi: 10.3390/sym13081517.
- [2] Y. Chen and J. Xie, "Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix," *Manage. Sci.*, vol. 54, no. 3, pp. 477–491, Mar. 2008, doi: 10.1287/mnsc.1070.0810.
- [3] S. Sreevathsa, "Bridging Technical Telemetry and Business Decision-Making through Data Product Management," *Univers. Libr. Innov. Res. Stud.*, vol. 3, no. 3, pp. 32–36, Aug. 2026, doi: 10.70315/uloap.ulirs.2026.0303006.
- [4] S.-B. Yang, S. Hlee, J. Lee, and C. Koo, "An empirical examination of online restaurant reviews on Yelp.com," *Int. J. Contemp. Hosp. Manag.*, vol. 29, no. 2, pp. 817–839, Feb. 2017, doi: 10.1108/IJCHM-11-2015-0643.
- [5] S. Consoli, L. Barbaglia, and S. Manzan, "Fine-grained, aspect-based semantic sentiment analysis within the economic and financial domains," in *2020 IEEE Second International Conference on Cognitive Machine Intelligence (CogMI)*, IEEE, Oct. 2020, pp. 52–61. doi: 10.1109/CogMI50398.2020.00017.
- [6] D. Tanna, M. Dudhane, A. Sardar, K. Deshpande, and N. Deshmukh, "Sentiment Analysis on Social Media for Emotion Classification," in *Proceedings of the International Conference on Intelligent Computing and Control Systems, ICICCS 2020*, 2020. doi: 10.1109/ICICCS48265.2020.9121057.
- [7] W. Zhang, X. Li, Y. Deng, L. Bing, and W. Lam, "A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 11, pp. 11019–11038, Nov. 2023, doi: 10.1109/TKDE.2022.3230975.
- [8] A. Tiwari, K. Tewari, S. Dawar, A. Singh, and N. Rathee, "Comparative Analysis on Aspect-based Sentiment using BERT," in *2023 7th International Conference on Computing Methodologies and Communication (ICCMC)*, IEEE, Feb. 2023, pp. 723–727. doi: 10.1109/ICCMC56507.2023.10084294.
- [9] P. Dominic, N. Purushothaman, A. S. A. Kumar, A. Prabakaran, J. Angelin Blessy, and J. A., "Multilingual Sentiment Analysis using Deep-Learning Architectures," in *2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, IEEE, Jan. 2023, pp. 1077–1083. doi: 10.1109/ICSSIT55814.2023.10060993.
- [10] M. Wankhade, A. C. S. Rao, and C. Kulkarni, "A survey on sentiment analysis methods, applications, and challenges," *Artif. Intell. Rev.*, vol. 55, no. 7, pp. 5731–5780, Oct. 2022, doi: 10.1007/s10462-022-10144-1.
- [11] S. Satyanarayana, S. Kilaru, and K. Venkatrao, "An Integrated Deep Learning and Reinforcement Learning Framework for Profit Maximization in Perishable Food Supply Chains," in *1st Engineering Data Analytics and Management Conference (EAMCON 2025)*, Springer Nature, 2025, pp. 156–171, December. doi: 10.2991/978-94-6463-978-0_15.
- [12] S. M. Zavattaro, P. E. French, and S. D. Mohanty, "A sentiment analysis of U.S. local government tweets: The connection between tone and citizen involvement," *Gov. Inf. Q.*, vol. 32, no. 3, pp. 333–341, 2015, doi: 10.1016/j.giq.2015.03.003.
- [13] F. J. Ramírez-Tinoco, G. Alor-Hernández, J. L. Sánchez-Cervantes, M. del P. Salas-Zárate, and R. Valencia-García, "Use of Sentiment Analysis Techniques in Healthcare Domain," in *Current Trends in Semantic Web Technologies: Theory and Practice*, Cham, 2019, pp. 189–212. doi: 10.1007/978-3-030-06149-4_8.
- [14] R. Lingam, "AI-Powered Framework for Evaluating Child-Friendly Mobile Applications," *Int. J. Hum. Comput. Intell.*, vol. 4, no. 4, pp. 535–549, 2025, doi: 10.5281/zenodo.15624307.
- [15] Y. Huang, C. M. Hall, and N. (Chris) Chen, "The sustainability characteristics of Michelin Green Star Restaurants," *J. Foodserv. Bus. Res.*, vol. 28, no. 2, pp. 219–244, Mar. 2025, doi: 10.1080/15378020.2023.2235258.
- [16] K. Dixit, "Custom Experience Analysis in the Hospitality Service Sector using AI-Based Hotel Review Analytics," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 5, no. 1, p. 720, Nov. 2025, doi: 10.48175/IJARSCT-29699.
- [17] M. Gon, "Local experiences on Instagram: Social media data as source of evidence for experience design," *J. Destin. Mark. Manag.*, vol. 19, p. 100435, Mar. 2021, doi: 10.1016/j.jdmm.2020.100435.
- [18] R. Palwe, "The Role of User Experience Design in Advancing Digital Sustainability," *Int. J. Sci. Res.*, vol. 14, no. 10, pp. 1168–1176, Oct. 2025, doi: 10.21275/SR251021070714.
- [19] O. Rohanian, S. Taslimipoor, R. Evans, and R. Mitkov, "WLV at SemEval-2018 Task 3: Dissecting Tweets in Search of Irony," in *Proceedings of The 12th International Workshop on Semantic Evaluation*, Stroudsburg, PA, USA: Association for Computational Linguistics, 2018, pp. 553–559. doi: 10.18653/v1/S18-1090.
- [20] Q. Gu, Z. Wang, H. Zhang, S. Sui, and R. Wang, "Aspect-Level Sentiment Analysis Based on Syntax-Aware and Graph Convolutional Networks," *Appl. Sci.*, vol. 14, no. 2, 2024, doi: 10.3390/app14020729.
- [21] T. Ranjan, A. Singh, R. Kumari, S. Swain, A. Bandyopadhyay, and A. K. Parida, "Multilingual Code-Mixed Sentiment Analysis in Hate Speech," *Scalable Comput. Pract. Exp.*, vol. 24, no. 4, pp. 873–882, Nov. 2023, doi: 10.12694/scpe.v24i4.2375.
- [22] C. P. Singh, "Enterprise-Grade AI-Driven Text Analytics and Insight Extraction Using Transformer-Based NLP Models," in *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, IEEE, Mar. 2026, pp. 1–6. doi: 10.1109/ISDFS69419.2026.11459059.
- [23] P. Sundaramoorthy and J. Lingam, "Enhancing Supply Chain Resilience and Efficiency with Large Language Models," in *2026 IEEE 18th International Conference on Computational Intelligence and Communication Networks (CICN)*, Manila, Philippines: IEEE, Jun. 2026, pp. 367–373. doi: 10.1109/CICN70047.2026.11594388.
- [24] N. A. S. Abdullah and N. I. A. Rusli, "Multilingual Sentiment Analysis: A Systematic Literature Review," *Pertanika J. Sci. Technol.*, vol. 29, no. 1, 2021, doi: 10.47836/pjst.29.1.25.
- [25] J. Wang, S. Oyama, M. Kurihara, and H. Kashima, "Learning an accurate entity resolution model from crowdsourced labels," in

- Proceedings of the 8th International Conference on Ubiquitous Information Management and Communication*, in ICUIMC '14. New York, NY, USA, NY, USA: ACM, Jan. 2014, pp. 1–8. doi: 10.1145/2557977.2558060.
- [26] J. P. Venugopal, A. A. V. Subramanian, G. Sundaram, M. Rivera, and P. Wheeler, “A Comprehensive Approach to Bias Mitigation for Sentiment Analysis of Social Media Data,” *Appl. Sci.*, vol. 14, no. 23, p. 11471, Dec. 2024, doi: 10.3390/app142311471.
- [27] G. V. Londhe, N. Jain, A. Kolhe, S. Deshmukh, A. Nanade, and S. Pillai, “Enhancing Restaurant Sentiment Analysis: A Comparative Study of Machine Learning Models and Word Embeddings,” in *2026 International Conference on Emerging Technologies and Future Innovations (ETFI)*, IEEE, Feb. 2026, pp. 1–7. doi: 10.1109/ETFI68128.2026.11484672.
- [28] Z. U. R. K and M. Giri, “Enhancing Hotel Services in the Industry 6.0 Era: Optimizing Customer Satisfaction through Sentiment Analysis,” in *2025 6th International Conference for Emerging Technology (INCET)*, IEEE, May 2025, pp. 1–6. doi: 10.1109/INCET64471.2025.11140059.
- [29] S. Abbas *et al.*, “Aspect Category Detection of Mobile Edge Customer Reviews: A Distributed and Trustworthy Restaurant Recommendation System,” *IEEE Trans. Consum. Electron.*, vol. 70, no. 1, pp. 2170–2177, Feb. 2024, doi: 10.1109/TCE.2023.3323334.
- [30] J. Zhu and Y. Cao, “A Study of Fusion Strategies for Self-Attention Enhanced Convolutional Neural Networks in Short Text Classification,” in *2024 6th International Conference on Communications, Information System and Computer Engineering (CISCE)*, IEEE, May 2024, pp. 587–592. doi: 10.1109/CISCE62493.2024.10653453.
- [31] B. Sunarko, U. Hasanah, and S. Hidayat, “Enhancing Restaurant Customer Review Analysis: Multi-Class Text Classification with BERT,” in *2023 6th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, IEEE, Dec. 2023, pp. 501–506. doi: 10.1109/ISRITI60336.2023.10467438.
- [32] N. Pleerux and A. Nardkulpat, “Sentiment analysis of restaurant customer satisfaction during COVID-19 pandemic in Pattaya, Thailand,” *Heliyon*, vol. 9, no. 11, p. e22193, Nov. 2023, doi: 10.1016/j.heliyon.2023.e22193.